Robots and Labour Market Dynamics in India

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Abstract

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Keywords: Robots; Employment; Wages & Salaries; Labour Market

JEL Classification: J23; J31; O33

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1. Introduction

Automation is reshaping labour markets worldwide, yet its consequences for developing economies remain poorly understood. This paper studies the impact of industrial robot adoption on employment, workforce composition, and wages in a developing country, India, which is facing one of the most significant employment challenges. India must generate approximately 7.85 million non-farm jobs annually to absorb its growing working-age population (Economic Survey, 2024). At the same time, the annual installation of industrial robots in the country has increased more than fourfold over the past decade, from 2,126 units in 2014 to 9,123 in 2025, making it the sixth-largest robot installer globally (IFR, 2025). The total stock of industrial robots in Indian manufacturing grew from approximately 1,500 units in 2009 to nearly 30,000 by 2023, a nearly twenty-fold increase. Therefore, understanding whether robots complement or replace human workers is crucial for evaluating the effects of ongoing technological change.

Task-based models of automation provide the theoretical foundation for our analysis. Acemoglu and Restrepo (2018, 2019) formalise two opposing forces: a *displacement effect*, whereby robots replace workers in automatable, routine tasks, reducing labour demand; and a *productivity effect*, whereby cost reductions from automation expand output and raise labour demand in non-automated tasks. The net employment effect depends on the relative magnitudes of these forces, which may vary systematically with the level of robot penetration. These models were developed and tested primarily in advanced economies characterised by high wages, rigid employment contracts, and ageing workforces. However, their predictions may not generalise to developing countries, where underlying labour market dynamics are substantially different (Brynjolfsson & McAfee, 2014; Diao et al., 2025; Maloney & Molina, 2019), especially in India, for the following reasons. First, surplus labour in such an economy can dampen wage pressure, which potentially limits the cost incentive to substitute robots for workers (Lewis, 2014). Therefore, the relative strength of the productivity effect and the displacement effect is likely to differ substantially compared to advanced economies. Second, the widespread use of contract workers — employed indirectly through third-party agencies — provides firms with an additional margin of flexibility in adjusting labour inputs as production processes become more automated (Bertrand et al., 2025). Third, shortages of skilled workers may constrain the extent to which automation can fully substitute for or complement labour. These structural features make India an

ideal and policy-relevant labour atory for studying the consequences of automation in a developing country context.

We combine two complementary data sources to study these questions at the industry level. Robot adoption is measured using annual shipment data from the International Federation of Robotics (IFR), which provides industry-level counts of newly installed industrial robots in India for the period 2009–2023. Labour market outcomes are constructed from the Annual Survey of Industries (ASI), a plant-level dataset of India's registered manufacturing sector. A key advantage of the ASI is its unusually rich disaggregation of the workforce: it separately records permanent male and female production workers, workers hired through third-party contractors, supervisory and managerial staff, and other employees, along with the wages and salaries paid to each group. This level of disaggregation enables us to study the consequences of robot adoption across the employee groups and on their wages. We aggregate plant-level ASI data to the two-digit industry level and match it to IFR data using a hand-constructed correspondence between IFR industry classifications (ISIC, 2008) and India's National Industrial Classification (NIC), yielding a balanced panel of ten manufacturing industries for 15 years.

A central challenge in estimating the causal effect of robot adoption is endogeneity. Industries that adopt robots may differ systematically from those that do not in ways that independently predict labour market outcomes. An industry anticipating strong future demand may simultaneously invest in robots and expand its workforce, while an industry facing labour shortages may adopt robots precisely because employment is already contracting. Industry and year fixed effects absorb time-invariant industry characteristics and aggregate macroeconomic shocks, but time-varying industry-specific demand and policy shocks still remain a concern. To address this, we also report estimates using the heteroskedasticity-based identification strategy of Lewbel (2012), which constructs internal instruments from the data without requiring external variation. We show that the instrument is strong and passes overidentification tests

Our findings reveal a rich and nuanced picture of the labour market consequences of robotisation in Indian manufacturing. We first document that the relationship between robot adoption and total employment is nonlinear. At low levels of robot penetration, the productivity effect dominates, consistent with output expansion and increased labour demand as predicted by task-based models (Acemoglu & Restrepo, 2018). However, as robot penetration intensifies, the displacement effect strengthens and eventually reverses employment growth around 10,250 units.

These effects are persistent, remaining statistically significant in subsequent years, suggesting that adjustments to production processes and workforce composition are gradual rather than immediate. This persistence is consistent with evidence from firm-level studies showing that the organisational adaptation required to integrate robots into production takes several years to complete (Koch et al., 2021; Bonfiglioli et al., 2024).

Further, we document a substantial heterogeneity in how different groups of workers are affected. Among permanent production workers, robot adoption drastically reduces the share of male workers but has little effect on the share of female workers. We interpret this differential effect as a reflection of the gender wage gap in India. Since firms pay higher wages to males than to females (Mahajan & Ramaswami, 2017; Deshpande et al., 2018; Blau & Kahn, 2017), they may have stronger incentives to substitute robots for male workers. This finding contrasts with evidence from advanced economies, where robot adoption tends to disproportionately affect female employment (Deng et al., 2023; Zuazu, 2022). The positive effect of robots on aggregate employment that we observed is driven entirely by an expansion of contract labour. This result is probably due to firms using flexible contract arrangements to manage the skill requirements and workforce adjustments associated with automation (Zhang et al., 2023; Bertrand et al., 2025). Moreover, the share of supervisory and managerial staff also declines due to robotisation. It implies that robots reduce the need for manual oversight of standardised production processes.

The wages and salaries effects of robot adoption are U-shaped. It reduces remuneration per employee at the initial stage, and it increases at the higher end of robot adoption. We also observe that the effect is heterogeneous among different groups and persists over time. For production workers — both permanent and contract workers — robot adoption initially places sustained downward pressure on wages. The wage decline is marginally larger for females than for males, where production workers (however, not statistically significant), and takes a turn around 10,000 units for robots. It suggests that while robots do not reduce the share of female workers in employment, they nonetheless share the burden of wage competition. Contract workers experience a sharp wage decline, with little upward movement in the upper tail, consistent with their weaker bargaining power and lower job security. The salaries of supervisory and managerial staff turn earlier than those of other workers and rise sharply, reflecting increased demand for workers with the technical and organisational skills to coordinate automated production systems.

This paper makes three contributions to the literature. *First*, we document a nonlinear effect of robotisation on employment (inverted-U-shaped) and wages (U-shaped). Existing empirical studies largely focused on estimating average linear effects of robot penetration on labour market outcomes (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018; Dauth et al., 2021; Autor & Dorn, 2013; Autor, Levy, and Murnane, 2003). In contrast, we show that the impact of robots on employment varies systematically across stages of technological diffusion. At low levels of robot penetration, the productivity effect dominates, leading to higher employment. Beyond a threshold level, displacement effects become stronger and reverse employment growth. This pattern may help explain why some studies find employment losses (Acemoglu & Restrepo, 2020), while others find neutral or modest effects (Graetz & Michaels, 2018) from robotisation. By formally identifying the nonlinear relationship, we provide new evidence that the labour market impact of automation is dynamic rather than static.

Second, this study contributes to the literature on the heterogeneous effects of automation on the labour market. We show that the aggregate positive employment effect of robots is driven mostly by an expansion of contract workers, hired through third-party agencies, who enjoy weaker employment protections, lower wages, and less job security (Bertrand et al., 2025). It suggests that firms in developing countries use flexible contract arrangements not merely as a cost-minimising strategy but as a structural complement to automation — substituting permanent workers with robots while expanding the contract workforce to automated production lines. Further, existing studies examined gender biases in robot adoption, primarily in advanced economies or cross-country settings (Deng et al., 2023; Zuazu, 2022). These studies identified that robots have a negative or moderate effect on female employment. Unlike those studies, our analysis reveals that robots disproportionately reduce the share of male permanent production workers without affecting the share of females. We provide an explanation rooted in the structure of India's gender wage gap (Mahajan & Ramaswami, 2017; Deshpande et al., 2018): since male workers command a wage premium in Indian manufacturing, firms face stronger cost incentives to substitute robots for male workers in automatable tasks. In addition, we find a decline in the share of employees in supervisory and managerial roles; however, their remuneration, unlike that of other workers, is relatively better.

Third, we provide causal evidence on the labour market effects of industrial robots in a large developing economy. The existing empirical literature is concentrated almost entirely on advanced economies: Acemoglu and Restrepo (2020) study US commuting zones, Dauth et al. (2021) study German local labour markets, Graetz and Michaels (2018) analyse a cross-country panel of high-income countries, and Koch et al. (2021) and Bonfiglioli et al. (2024) use firm-level data from Denmark and several European countries, respectively. Maloney and Molina (2019) and Diao et al. (2021) raise theoretical concerns about whether the findings from these settings extend to developing countries, but direct empirical evidence remains scarce. Our results demonstrate that the structural features of developing-country labour markets — particularly the prevalence of contract labour, the gender wage gap, and surplus labour — generate adjustment margins absent in advanced-economy settings, producing effects on workforce composition that cannot be extrapolated from existing evidence.

The remainder of the paper is organised as follows. Section 2 provides a review of the literature on the topic of interest. Section 3 describes the data sources and the construction of key variables. Section 4 presents the empirical framework, including the identification strategy. Section 5 reports the main results on employment, workforce composition, and wages, along with heterogeneity analysis and robustness checks. Section 6 concludes the study.

2. Review of Literature

Across the literature, a strong and consistent consensus emerges that industrial robots and related automation technologies do not primarily reduce total employment, but instead reorganize labour markets through productivity-driven structural change. However, the studies differ in scope and level of analysis, ranging from firm-level mechanisms to national institutions and global spillovers, which together provide a layered understanding of how automation reshapes employment.

At the country level, evidence from China and the United States highlights a common pattern of employment restructuring rather than net job destruction. In China, robot adoption enables the coexistence of labour and automation because productivity gains and firm expansion offset the displacement of routine workers, although it significantly increases demand for skilled labour and intensifies the need for reskilling policies (Du et al., 2025). Similarly, in the United

States, the combined diffusion of robotics, AI, ICT, and IoT reshapes job types rather than producing widespread permanent unemployment, with routine occupations most exposed but offset by new opportunities for highly skilled labour driven by innovation and productivity growth (Khakbaz & Malmir, 2026).

Extending beyond national contexts, cross-country evidence emphasizes that automation outcomes are not technologically deterministic but are strongly mediated by institutional and cultural conditions. Economies with more flexible, innovative, and learning-oriented systems are better able to absorb technological change without persistent increases in unemployment (Du et al., 2026). This institutional perspective is reinforced by sectoral evidence from manufacturing, where robots consistently reorganize employment toward higher-skilled tasks rather than reducing it outright, as productivity improvements and output expansion generate compensating labour demand (Elder et al., 2025).

At the firm level, the literature further highlights the endogenous and interactive nature of automation adoption. Rising labour costs encourage firms to adopt robots, while automation simultaneously enhances productivity and can support employment growth through business expansion, jointly shifting labour demand toward more skilled occupations (Jung and Lim, 2020). More specifically, Jung and Lim (2020) indicate that the simultaneous increase in unit labour costs and hourly compensation induces automation, which, in turn, leads to a reduction of unit labour costs and an increase in hourly compensation, implying that the productivity-enhancing effect exceeds the wage-increasing effect of industrial robots. At the same time, Mao and Guo (2025) examine Chinese listed firms. Their results show that the capital spillover effect of customer robot adoption reduces the employment of suppliers, especially for supplier firms that are in low-tech industries, highly labour-intensive, located in regions with less market segmentation, and geographically close to each other. Therefore, the effects are not confined to individual firms but extend through supply chain networks, where productivity gains spill over to connected firms and partially offset displacement effects, depending on firms' positions within production systems and their ability to capture efficiency gains (Mao and Guo, 2025).

Beyond employment quantities, several studies emphasize broader socio-economic and behavioral consequences. Technological shocks are shown to reshape labour ideology by increasing perceived job insecurity while simultaneously encouraging greater investment in skills, adaptability, and lifelong learning, indicating that automation also transforms workers'

expectations and attitudes toward work (Ding et al., 2026). At the same time, while robot adoption generally improves productivity and expands employment opportunities, its benefits are not automatically distributed equally. Without adequate education and labour market support, automation can intensify income inequality by disproportionately favouring high-skilled workers, making inclusive adjustment dependent on effective policy frameworks. Therefore, without proper institutional support, income disparities may worsen (Xin & Ye, 2024; Wang et al., 2024).

Across advanced manufacturing economies such as Japan, Germany, and China, similar structural patterns are observed: robots reduce routine labour demand but sustain or increase overall employment through productivity gains and workforce reallocation toward higher-skilled roles (Ni and Obashi, 2021; Graf and Mohamed, 2024; Tang et al., 2021). Graf & Mohamed (2024), who analyse 14 German manufacturing industries, find a positive relationship between robotization and employment in their upstream GVC trade partners. Tang et al. (2021) use inverse probability of treatment weighting (IPTW) and propensity score matching (PSM) difference-in-differences (DID) to find that robot adoption encourages firms to hire more highly skilled and highly educated workers. Ni and Obashi (2021) find that industry-level adoption of robots positively affects both firm-level job creation and job destruction rates, with an overall negative impact on firms' net employment growth. The results imply simultaneous labour displacement and the emergence of new jobs due to robotization-led technological change.

More broadly, global evidence confirms that automation primarily reorganizes employment rather than generating widespread technological unemployment, with outcomes shaped by the balance between displacement and productivity-driven job creation and the strength of reskilling institutions (Sequeira et al., 2021; Sharfaei & Bittner, 2024). In China, this transformation is further reinforced by a "technology creation" mechanism in which innovation and industrial upgrading offset displacement by generating new skilled employment opportunities (Zhang et al., 2024).

Finally, spillover and local adjustment studies extend the analysis beyond national and firm boundaries. Automation in advanced economies can transmit through global value chains, reducing demand for low-skilled labour in developing countries while simultaneously creating new opportunities in more skill-intensive sectors, depending on structural upgrading capacity (Kugler et al., 2026). At the local level, robotization primarily operates through task reallocation rather than job destruction, as routine activities are automated and workers shift toward

complementary non-routine roles, with outcomes depending on local adaptability and skill composition (Caselli et al., 2026).

Overall, despite differences in emphasis and level of analysis, the literature converges on a unified conclusion: automation reshapes employment systems rather than contracting them, with labour market outcomes determined by productivity gains, skill formation, institutional adaptability, and the capacity of economies and firms to manage structural transformation.

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3. Data

This study combines data from two sources. One dataset from the International Federation of Robotics (IFR) and another from the Annual Survey of Industries (ASI). Both datasets are merged at the industry level for the period 2009-2023.

3.1. Robot Data

We obtain robot data from IFR, the principal global source of harmonised statistics on the adoption of industrial robots. Industrial robots are defined by ISO 8373 as automatically controlled, reprogrammable, multipurpose manipulators, programmable in three or more axes, and designed for use in industrial automation processes. Industrial robots mainly perform tasks such as assembling, dispensing, handling, processing, and welding, all of which are widely used in manufacturing. This dataset provides industry-level information on the number of robots installed every year in the country. IFR industrial classification code, IFR Class, and industry name are also provided in the data. This dataset has been widely used in the automation and labour market literature (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020; Dauth et al., 2021; Klenert et al., 2023). We use the IFR industry classification (IFR Class) to construct a concordance with Indian NIC codes.

3.2 Annual Survey of Industries

Our second source is the ASI, which provides plant-level information on India's organised manufacturing sector. The ASI is conducted annually by the Ministry of Statistics and Programme Implementation (MoSPI), which covers registered manufacturing establishments operating under the Factories Act, 1948. In general, the survey includes factories employing 10 or more workers with the aid of power or 20 or more workers without power. It covers a wide range of manufacturing industries, including food processing, textiles, chemicals, metals, machinery, and transport equipment, and represents the core of India's formal manufacturing sector.

This dataset provides detailed establishment-level employment information. The ASI provides a detailed breakdown of employment by different categories of workers. It distinguishes between workers i) directly employed in the production, which is further divided into male and female workers[1]; ii) workers employed through third-party agencies (contract workers); iii) supervisory & managerial staff; and iv) other employees. This categorical breakdown allows us to examine how robots differentially affect distinct segments of the workforce. In addition, the dataset provides wages and salaries for each employee category, allowing us to examine the differential

[1] Since 2024, transgender category is added. However, we did not use that classification due to lack of enough observations.

impact of robots on wages and salaries separately for each worker category. ASI follows the NIC industrial level classification, which will be used to merge with the IFR data.

3.3 Industry Concordance and Sample Construction

Since robot data uses IFR Class as the industry code, and ASI uses NIC industrial code, we establish a manual correspondence between the two systems at the 2-digit level. The concordance table is presented in Table 1A in the appendix. Further, we include only plants that are operational at the time of survey, a total of 7,22,758 plants during the study period. We then aggregate plant-level observations to the two-digit industry–year level. The final data has 10 industries for the period 2009 to 2023. All monetary variables are deflated with the wholesale price index to ensure comparability across years.

One important data alignment issue arises from the difference in reference periods between the two sources. The IFR data are reported on a calendar year basis (Jan to Dec), and ASI follows the financial year (Apr to March). To ensure temporal alignment, we match the IFR data in December with the next year's ASI March data. For example, the 2010 calendar year IFR data is matched with the 2010-11 financial year ASI data. Table A2 in the appendix explains variable construction, and Table 1 presents summary statistics of those variables.

Table 1: Summary Statistics

Variable	Observation	Mean	S D	Min	Max
Robot	150	0.90	2.59	0.00	15.87
Male	150	12.26	1.03	9.98	13.94
Female	150	10.11	1.59	6.80	13.29
Contract	150	12.10	1.03	9.73	13.36
Managerial	150	10.91	1.02	8.53	12.26
Male Share	150	0.32	0.04	0.24	0.42
Female Share	150	0.07	0.07	0.00	0.25
Contract Share	150	0.29	0.08	0.11	0.42
Managerial Share	150	0.10	0.02	0.05	0.17
Wages & Salaries	150	25.59	1.18	22.20	27.30
Male Wages	150	24.35	1.18	21.08	26.01
Female Wages	150	21.70	1.57	18.22	25.05
Contract Wages	150	23.68	1.14	20.70	25.63
Managerial Wages	150	24.56	1.23	20.82	26.45
Size	150	27.82	1.39	24.02	30.11
Borrowing	150	0.34	0.16	0.14	0.93
Investment	150	1.41	0.28	1.12	2.38

Note: Robots refers to the number of robots installed divided by 1000

3. Empirical Framework

This section presents the estimation models to investigate the impact of robots on labour market outcomes. Specifically, we estimate the relationship between robotisation in industries and employment & wage outcomes for different categories of employees.

3.1. Baseline specification

To estimate the impact of robots on labour market outcomes, we estimate the following model:

$$y_{i,t} = \alpha + \beta\, Robots_{i,t-1} + X_{i,t} + \emptyset_i + \gamma_t + \varepsilon_{i,t} \qquad (1)$$

Where, $y_{i,t}$ represents labour market outcomes in industry *i* at time *t*. These include total employment and its sub-categories or different worker groups. Total employment is measured as the ratio of total man-days worked to the number of working days. It includes production workers, supervisory & managerial staff, and other employees. The production workers are further classified into permanent male workers, permanent female workers, and contract workers. We also use the share of their sub-groups in total employment as another set of dependent variables.

Robots refers to the number of robots installed divided by 1000, constructed using industry-level data from the International Federation of Robotics (IFR). The IFR reports annual shipments of industrial robots by industry. The impact of robots may be reflected in employment with a delay, since it takes time to reorganise production processes and adjust the workforce. So, we use a one-year lagged robot measure in our model.

$X_{i,t}$ is a vector of control variables that capture industry characteristics such as the size of the industry (measured as the log of fixed capital), the borrowing-to-fixed capital ratio, and the investment-to-fixed capital ratio. $\emptyset_i$ represents industry fixed effects that control for time-invariant unobserved industry characteristics such as technological intensity, production complexity, and capital requirements. γ_t represents year fixed effects that capture macroeconomic shocks affecting all industries. ε is the error term.

To study potential nonlinear effects, we augment the above model specification with a quadratic term of the robot measure:

$$y_{i,t+k} = \alpha + \beta_1 \, Robots_{i,t-1} + \beta_2 \, Robots^2{}_{i,t-1} + X_{i,t} + \emptyset_i + \gamma_t + \varepsilon_{i,t+k} \qquad (2)$$

An inverted-U relationship between robotisation and employment arises when $\beta_1 > 0$ and $\beta_2 < 0$. Further, we formally test this nonlinear relationship using the Lind–Mehlum (2010) test for inverted-U shaped relationships. k takes a value from 0 to 5. This specification also allows us to examine whether robotisation has persistent effects on employment and wages & salaries over time.

All the labour market data are obtained from the Annual Survey of Industries (ASI). We use all labour market variables in log form in the econometric analysis, so that coefficients can be expressed in percentage terms. The main interest of these analyses is the coefficient β, which captures the relationship between robotisation and labour market outcomes.

3.2 Identification

One potential issue in estimating our models is endogeneity due to omitted variable **bias**. Certain factors can affect both labour market outcomes and robotisation. For example, industries experiencing stronger demand or a higher future demand may both adopt robots more rapidly and experience different employment dynamics. In a similar manner, government policies may affect investment and employment differently for different industries. Failure to adequately control for such factors in the model may provide biased estimates.

To address this concern, we implement an instrumental variable approach proposed by Lewbel (2012). It is a heteroskedasticity-based identification strategy that generates internal instruments by exploiting heteroskedasticity in the data. Specifically, instruments are constructed by interacting the residuals from the first-stage regression with demeaned exogenous variables. These generated instruments are then used within a two-stage least squares framework to estimate the causal effect of robot adoption on labour market outcomes. This approach allows identification even in the absence of conventional external instruments.

The validity of the instruments relies on the assumption that the covariance between the exogenous regressors and the product of heteroskedastic errors is non-zero, while the instruments remain uncorrelated with the structural error term. To assess instrument validity, we report Hansen's J-test statistics for overidentifying restrictions. The inclusion of industry and year fixed effects, along with an instrumental variable approach, helps mitigate concerns about endogeneity and strengthens the causal interpretation of the estimated relationship between robotisation and labour market outcomes.

4. Results

4.1. Descriptive analysis

Figure 1 presents the evolution of the total industrial robot stocks in the Indian manufacturing sector between 2009 and 2023. It shows a sustained increase in the number of robots installed over the period. In 2009, the total number of robots installed was approximately 1,500 units. Since then, it has gradually increased and accelerated after 2013. From 2014 onwards, robot growth becomes more prominent, reaching nearly 30,000 units by 2023, more than a twenty-fold increase compared to the beginning of the sample period. Overall, robot adoption in the Indian manufacturing sector has increased exponentially over the past decade. This trend motivates the empirical analysis to examine how increasing robotisation affects employment and wages in the Indian labour market.

Figure 2 illustrates the total installed robot stock across manufacturing industries. It shows a considerable heterogeneity in adoption across the sectors and is concentrated in a few industries. The automotive sector witnessed the highest level of robotisation, with robot stocks increasing rapidly from the early 2010s and reaching nearly 20,000 units by 2023. These robots might be used for tasks such as welding, assembly, and material handling (Acemoglu and Restrepo, 2017). Similarly, other capital-intensive industries, such as plastic and chemical products, metal manufacturing, and electrical and electronics equipment, show stronger adoption growth over the sample period. In contrast, traditionally labour-intensive industries such as textiles, wood and furniture, and paper products show only modest increases in robot stocks and continued reliance on manual labour in production processes. Further, a visible growth in robots is observed across other industries, such as food and beverages, electrical equipment, and transport equipment, consistent with broader trends.

Figure 1: Evolution of Industrial Robot Stocks in Indian Manufacturing

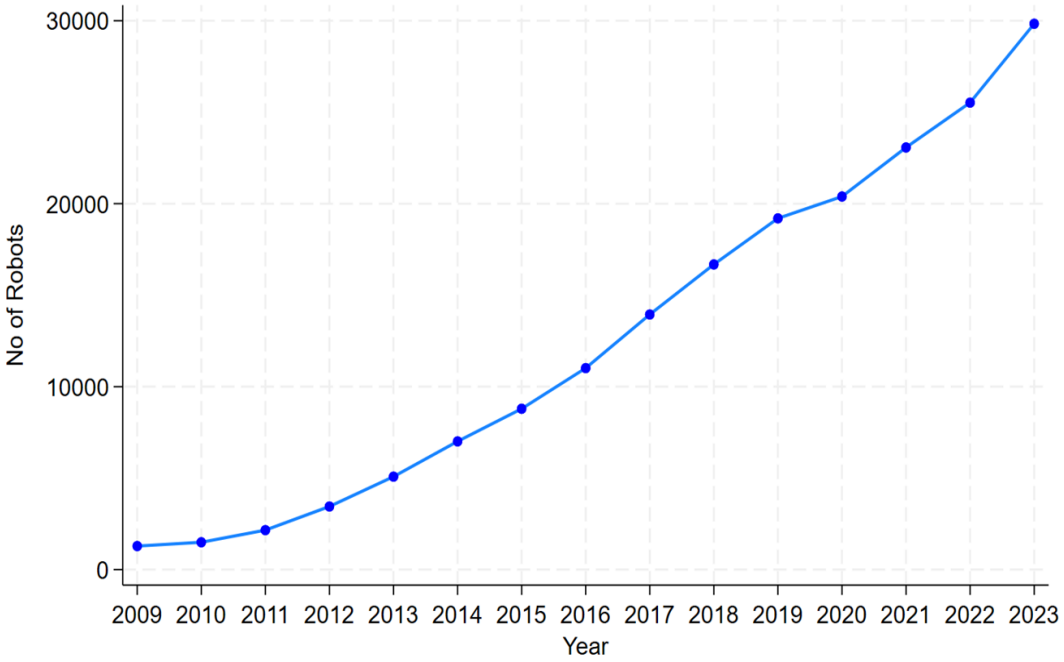


Figure 2: Total robots installed in each industry

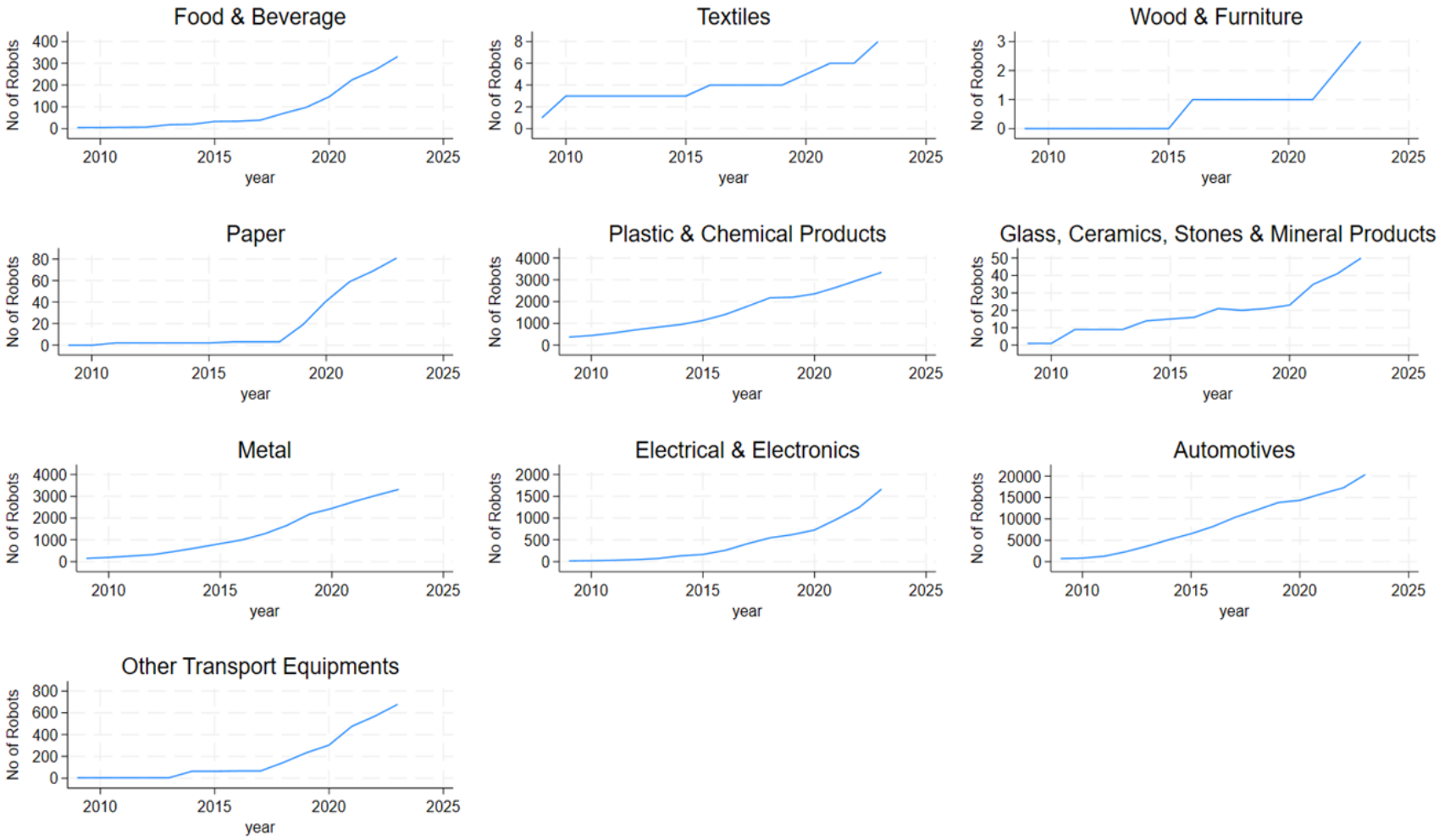


Table 2: Robot adoption and employment

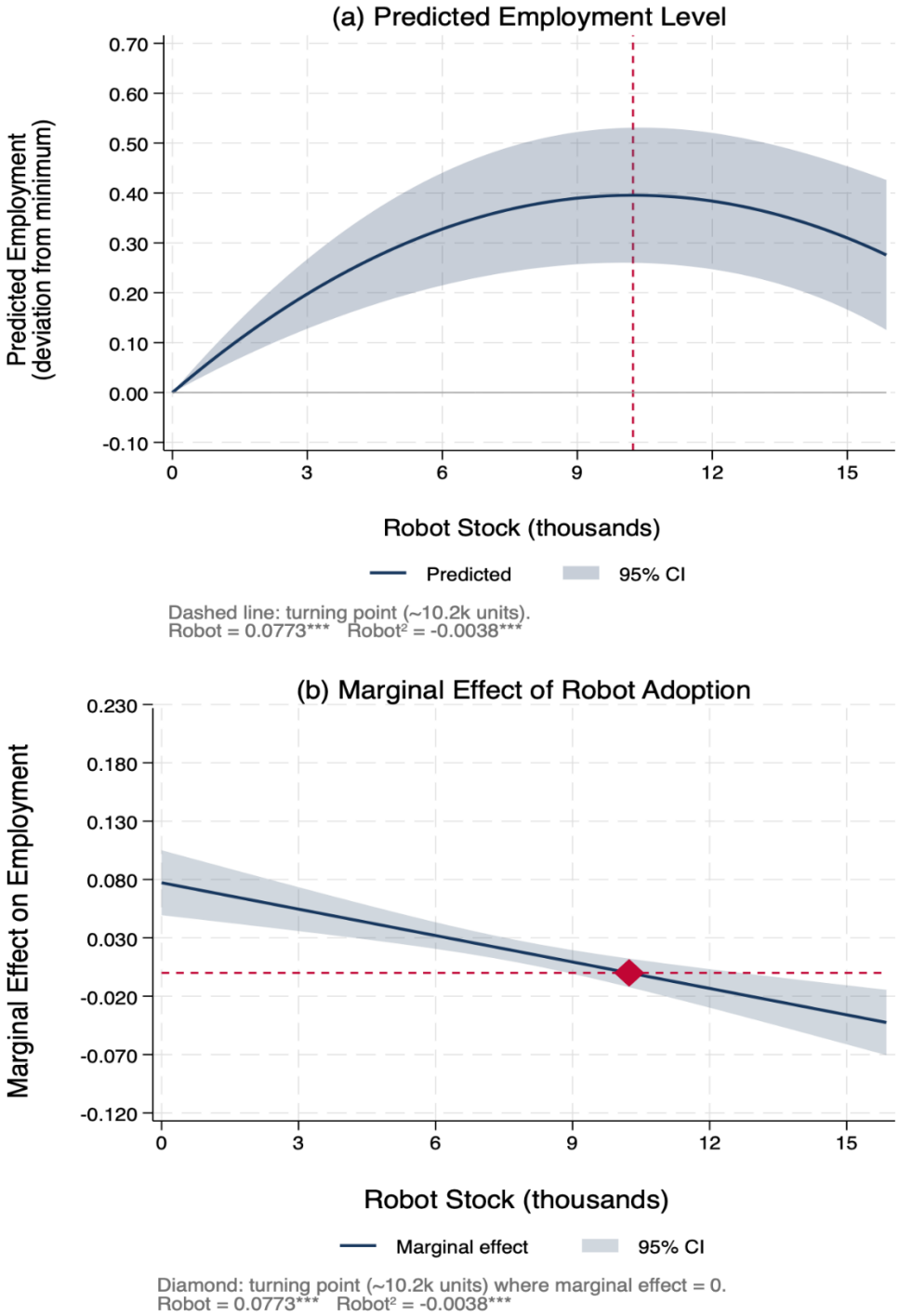
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
VARIABLES	Employment		ΔEmployment		Employment	
Robotsq					-0.00377**	-0.00246***
					(0.00156)	(0.000495)
Robot	0.0184**	0.00926***	-0.00535**	-0.00325*	0.0773**	0.0506***
	(0.00794)	(0.00323)	(0.00230)	(0.00191)	(0.0268)	(0.00812)
Constant	7.951	2.130	-2.635	-1.357	9.719*	6.046***
	(5.561)	(2.236)	(1.927)	(1.307)	(4.406)	(1.719)
Observations	150	150	140	140	150	150
R-squared	0.482	0.995	0.442	0.484	0.575	0.996
Number of indcode	10		10		10	
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J p-value		0.217		0.138		0.292
Turning Point (IV)					10.24	10.27
Joint p-value (IV)					0.0214	1.54e-10
Lind-Mehlum U-test p-value (IV)					0.0265	8.51e-06

Note: The table shows the relationship between employment and robots. Columns 1 and 2 report employment as the dependent variable for OLS and IV regressions, respectively. Columns 3 and 4 present the OLS and IV regressions, with the change in employment as the dependent variable. In addition, columns 5 and 6 show the non-linear relation between robots and employment. Regression includes industry controls, industry fixed effects, and year fixed effects. For IV estimation, use the Lewbel (2012) method. Robust standard errors are reported in parentheses at 1%, 5%, 10% levels of significance denoted as ***, **, and *, respectively.

4.2. Robots and Employment

Table 2 studies the relationship between robot adoption and employment in Indian manufacturing industries. The odd-numbered columns report ordinary least squares (OLS) and even-numbered columns report instrumental variable (IV) estimators. All specifications include industry and year fixed effects as well as a set of industry-level controls. Columns 1 and 2 report the OLS and IV estimation results of equation 1 with $k = 0$ to examine the impact of robots on the log of employment, respectively. The results indicate a positive and statistically significant relationship between robotization and employment. The OLS and IV estimates suggest that an increase of 1,000 units in robot stock is associated with approximately a 1.8% and 0.9% increase in employment, respectively. This positive nexus is consistent with the dominance of the productivity effect of automation, whereby robots improve production efficiency and expand output, thereby increasing labour demand.

Figure 3: Robots and employment



To understand the rate at which employment is growing, we use the change in the log of employment (rather than in levels) in equation 1. We find, in Columns 3 and 4, a negative

coefficient for our robot measure, suggesting that although employment is increasing due to robotisation, the rate of increase is declining. In other words, a further increase in robot stock is associated with a lower employment growth rate. This pattern of employment-robot relationship further motivated us to explore the nonlinear relationship between both variables.

For that, we estimate equation 2 with a quadratic term for the robot measure and present our findings in Columns 5 and 6. It shows that the coefficient on the robot measure is positive and the coefficient of its squared term is negative and statistically significant. It means there is an inverted-U relationship between robotisation and employment. The nonlinear pattern is consistent with theoretical predictions from task-based models. At low levels of robot adoption, the productivity effect of automation dominates, improving efficiency and reducing costs, allowing firms to expand production and demand more labour. However, as robot penetration increases, the displacement effect becomes more pronounced, reducing employment growth.

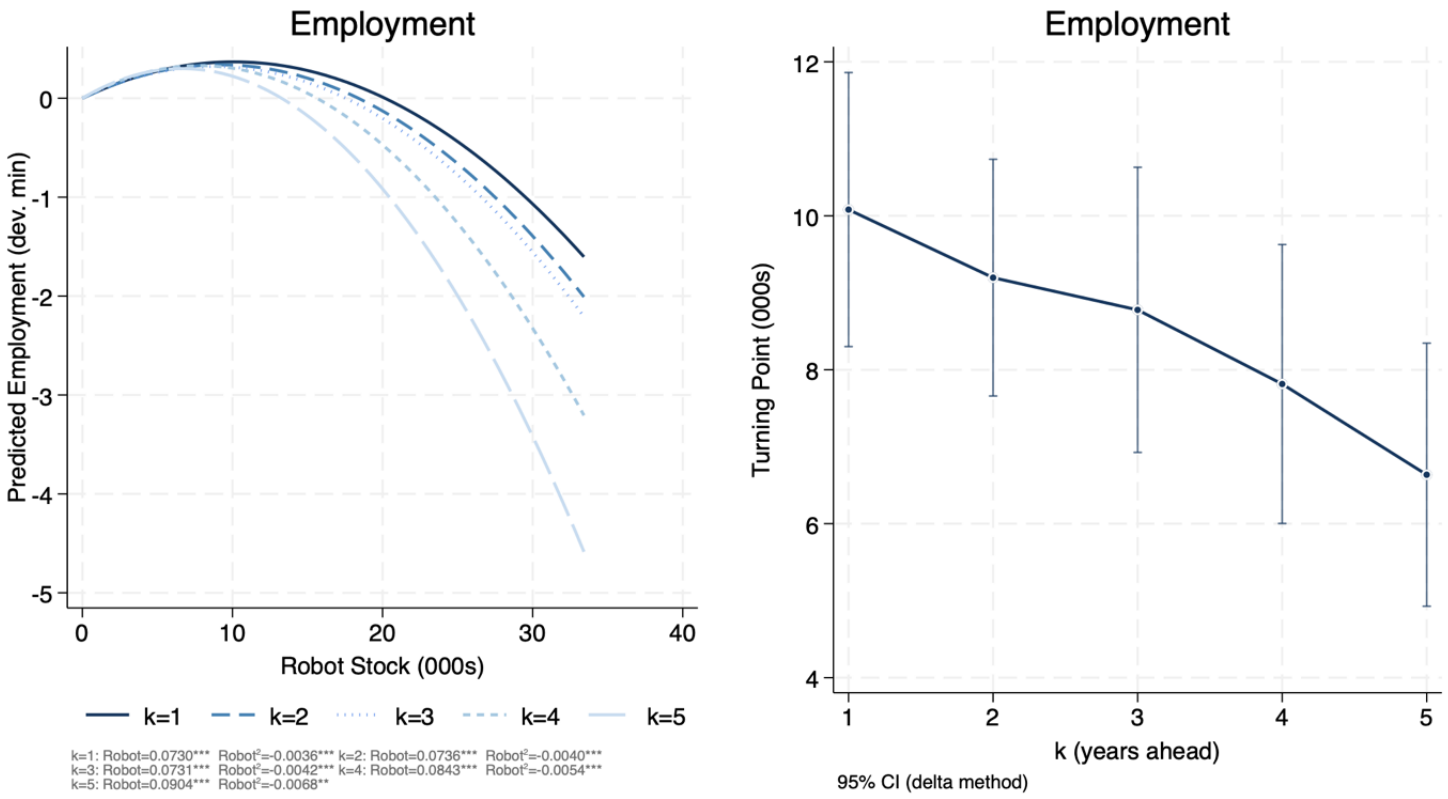
The estimated turning points from the OLS and IV specifications are 10,240 and 10,270 units, respectively, indicating that employment initially increases with robots until this threshold is reached, then declines thereafter. In our data, only the automotive sector crosses this threshold. Further, we formally test for an inverted-U shape using the Lind–Mehlum U-test. The test rejects the null hypothesis of a monotonic relationship and confirms the presence of a statistically significant inverted-U relationship between robots and employment in the Indian manufacturing sector. Also, the Hansen-J test confirms the instrument's validity in IV regression. The results of the OLS regression are graphically illustrated in Figure 3. The top panel presents the predicted employment deviation from the minimum-adoption industry obtained using equation 2. It shows an inverted-U-shaped relationship vividly. The bottom panel presents its slope.[2]

Moreover, it often takes some time to adjust and integrate new technologies into the production process. Therefore, the labour market effects of robot adoption could materialise gradually rather than instantaneously, or persist for a longer period. To examine these responses, we estimate equation 2 for $k = 1$ to 5 and present OLS results in Figure 4. The left panel presents

[2] The rest of our analysis is carried out by using OLS. Although our IV estimation result provides qualitatively similar results, over-identification test fails in some estimations. The IV results of our main analysis are presented in Figure A1 to A3 (appendix).

the predicted employment deviation from the minimum-adoption industry for different values of k, and the right panel shows the turning point with a 95% confidence interval. All curves initially rise and then fall, indicating that the nonlinear pattern continues beyond $k = 0$. Further, as k increases, the peak reaches earlier, and the downward part of the curve becomes steeper. It implies that the negative effects intensify over time. Overall, the results provide evidence of the persistent effects of robots on employment.

Figure 4: Persistence of Robot Effect on Employment



Left: predicted nonlinear curves; Right: turning point path

The above results reveal that robotisation has a significant effect on total employment in the Indian manufacturing sector. However, it does not provide insight into which categories of workers are more affected. Therefore, we extend our analysis to examine how robot adoption influences employment across different employee groups. Specifically, we investigate the impact of robots on the total number of employees in each group and on their share of total employment.

For this purpose, we estimate different specifications of equation 2 using the total number of employees in each employee category or their share of total employment as the dependent variable.

The first row of Figure 5 presents the predicted share of each employee category in total employment, and the second row presents the number of employees in each group. The shaded region represents 95% confidence intervals, and the vertical line indicates the turning point. The results indicate substantial heterogeneity in the effects of robot adoption across the groups. The share of permanent male production workers declined significantly due to robotisation, and it hardly rose at the high tail. When we compare both rows on male workers, this fall can be split into two parts: i) the initial fall before the turning point (around 9,000 units of robots), which is not due to not hiring male employees, but rather the proportion of hiring is significantly lower compared to the total employment increase. Intuitively, a 9000 units of robots by the lowest adopted industry increases male employment around 20%; however, the total employment increases around 40% (compare with figure 3), and ii) the drop after the turning point – both male workers and total employment fall with a relatively higher drop in male workers. This portion of the curve is relatively flat, indicating that both male workers and total employment fall. Intuitively, a further installation of 6,000 units of robots from the turning point by the lowest adopted industry reduces 10% of both male workers (20%−10%) and total employment (40%−30% in Figure 3).

The robotisation has no statistically significant effect on the share of female workers. This result is due to both female workers and total employment increasing at the same rate. The adoption of robots by the lowest adopted industry of 9,200 units (turning point) increases both female workers and total employment by around 40%. After the turning point, the share of female workers increases due to a relatively higher drop in total employment. While comparing the magnitude of both male and female employment, female employment registers a higher percentage increase at each level of robot stocks. We interpret this result as firms substituting male workers with robots, since male workers are relatively more highly paid than female workers. There is ample evidence for a gender wage gap in India (Mahajan and Ramaswami, 2017; Deshpande et al., 2018).

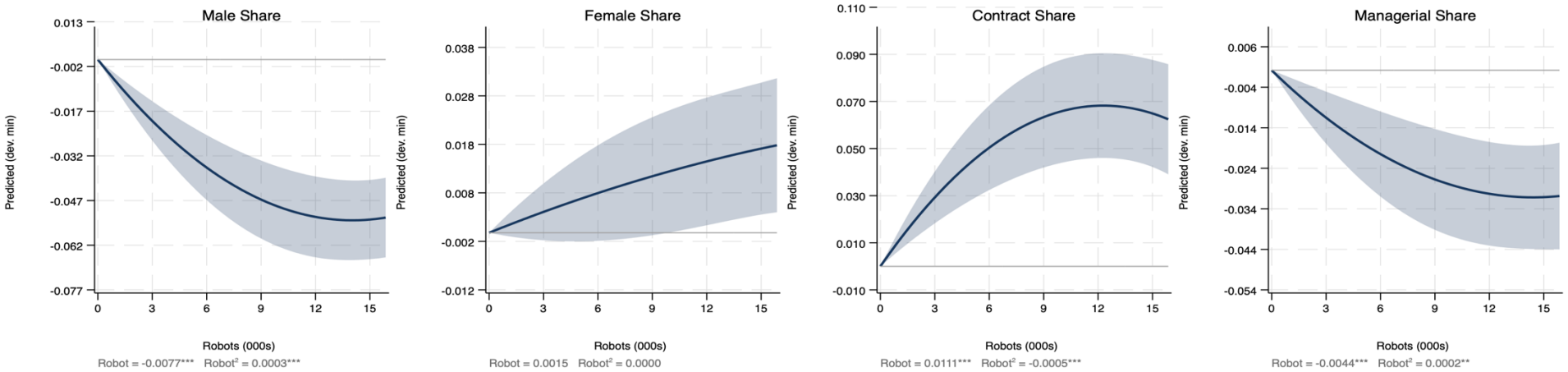
The pattern for contract workers is distinctly different from that of male and female workers. There is a consistent increase in the share of contract employees due to robotisation, except at the extreme right tail. The peak in contract worker growth is observed around 10,700

units of robots. Till the point, contract workers are increasing at a higher rate than total employment. Intuitively, an additional 10,700 units installed by the lower adopted industry in our data register 65% increase in contract workers, whereas total employment increases only 40% (compare with figure 3). After the turning point, the drop in employment of contract workers is almost equal to the drop in total employment; hence, their share is flat-curved. The key takeaway from these results is that industries that are adopting robots are increasingly relying on contract labour. They use them, contract workers, to maintain flexibility in adjusting labour inputs as production processes become more automated. The positive effect on total employment observed in the previous analysis (Table 1 and Figure 3) is mostly due to an increase in contract workers in the workforce.

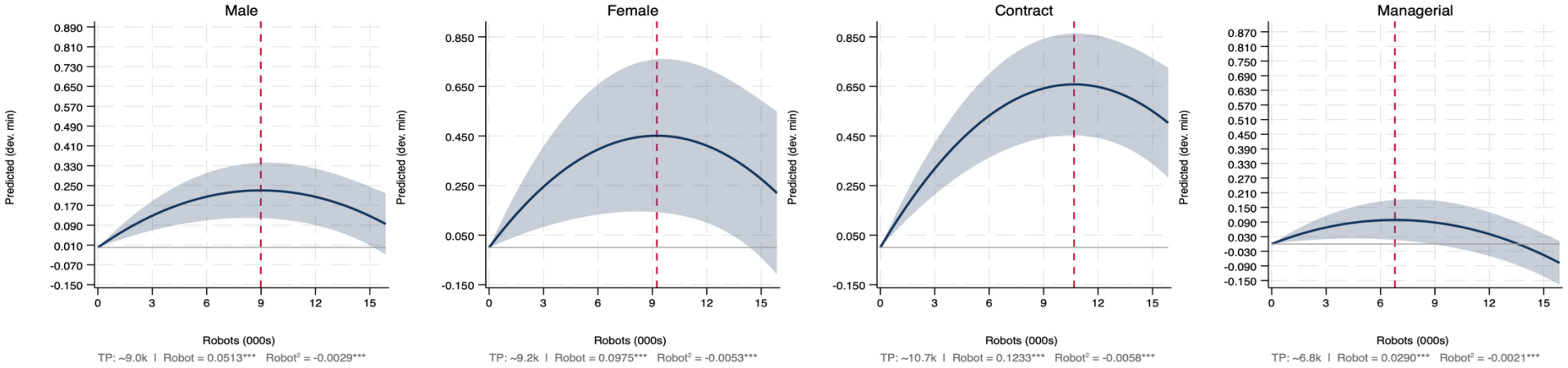
Moving towards the results for supervisory & managerial staff, a turning point appears around 6,800 units of robots, which is earlier than for other sets of workers, and the impact becomes statistically insignificant afterwards. The magnitude of the initial increase is relatively smaller compared to other groups, and therefore, their share of total employment drops drastically. Again, this decline is not due to layoffs but to stagnant hiring and an increase in the total number of employees. This stagnation in hiring may be due to robots reducing the need for certain supervisory or administrative roles as production processes become more standardised and technology-driven.

Taken together, the labour market effects of robotisation in the Indian manufacturing sector operate through increasing total employment and through changes in workforce composition. In particular, robot adoption appears to reduce the share of permanent employees while increasing the reliance on contract labour. Further, we studied the persistence of these effects. Figure 6 reports the result for $k = 2$ and $k = 4$ along with $k = 0$ for comparison. We document evidence for the persistence of the robot effect on the employment of different worker groups.

Figure 5: Nonlinear Effects of Robot Adoption on Workforce Composition

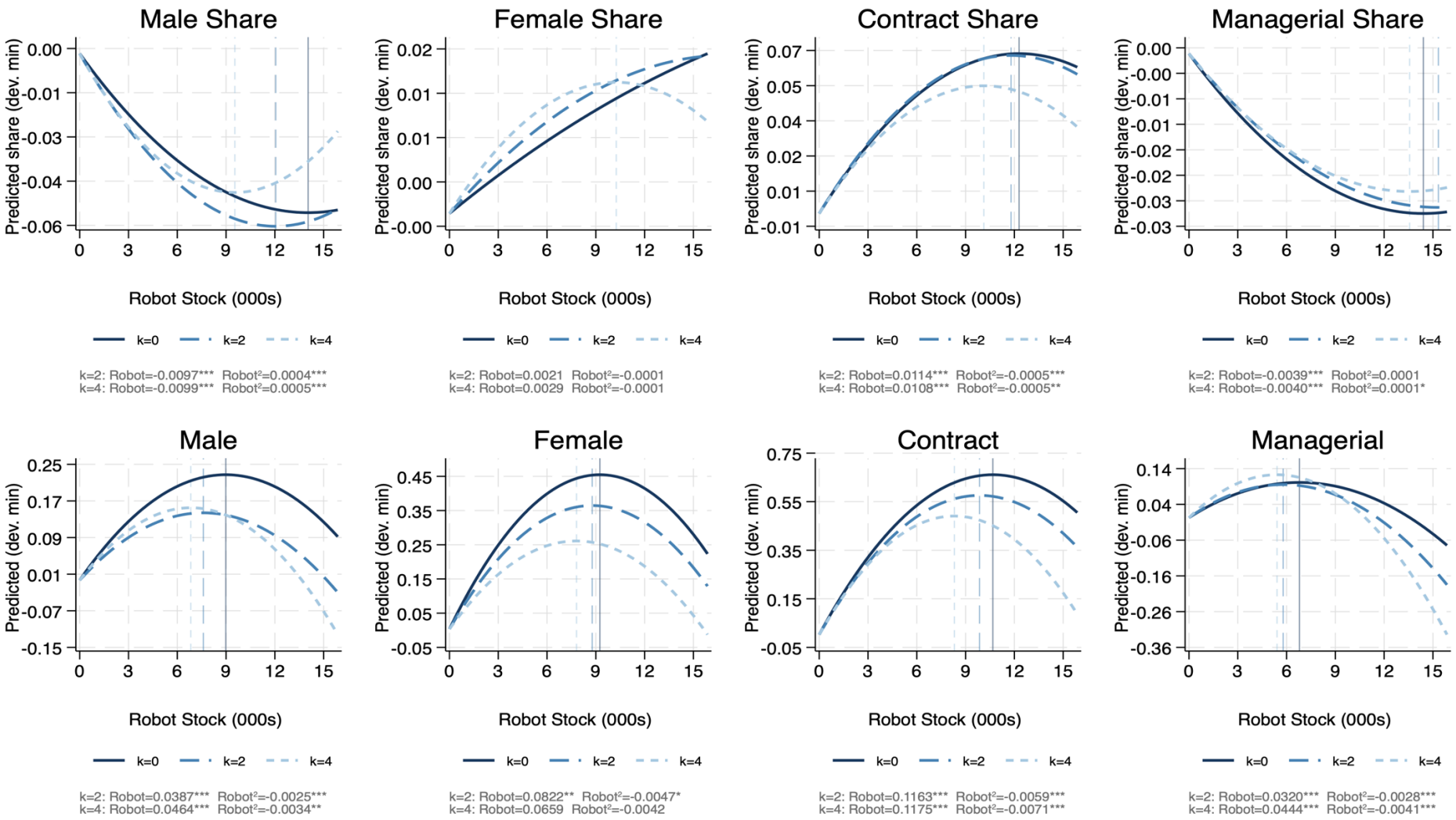


Y-axis: deviation from lowest-adoption industry.
Shaded band: 95% CI (delta method). * p<0.1 ** p<0.05 *** p<0.01



Y-axis: deviation from lowest-adoption industry. Dashed line: turning point.
Shaded band: 95% CI (delta method).

Figure 6: Persistence of the robot's impact on different worker groups



Predicted deviation from minimum-adoption industry.

4.3. Robots and Wages & Salaries

The previous subsections show that robot adoption not only changes total employment but also alters workforce composition, reducing the share of permanent workers while increasing reliance on contract labour. These changes may translate into wage and salary differences across employee groups. This subsection examines the impact of robots on wages and salaries across employee categories using equation 2.

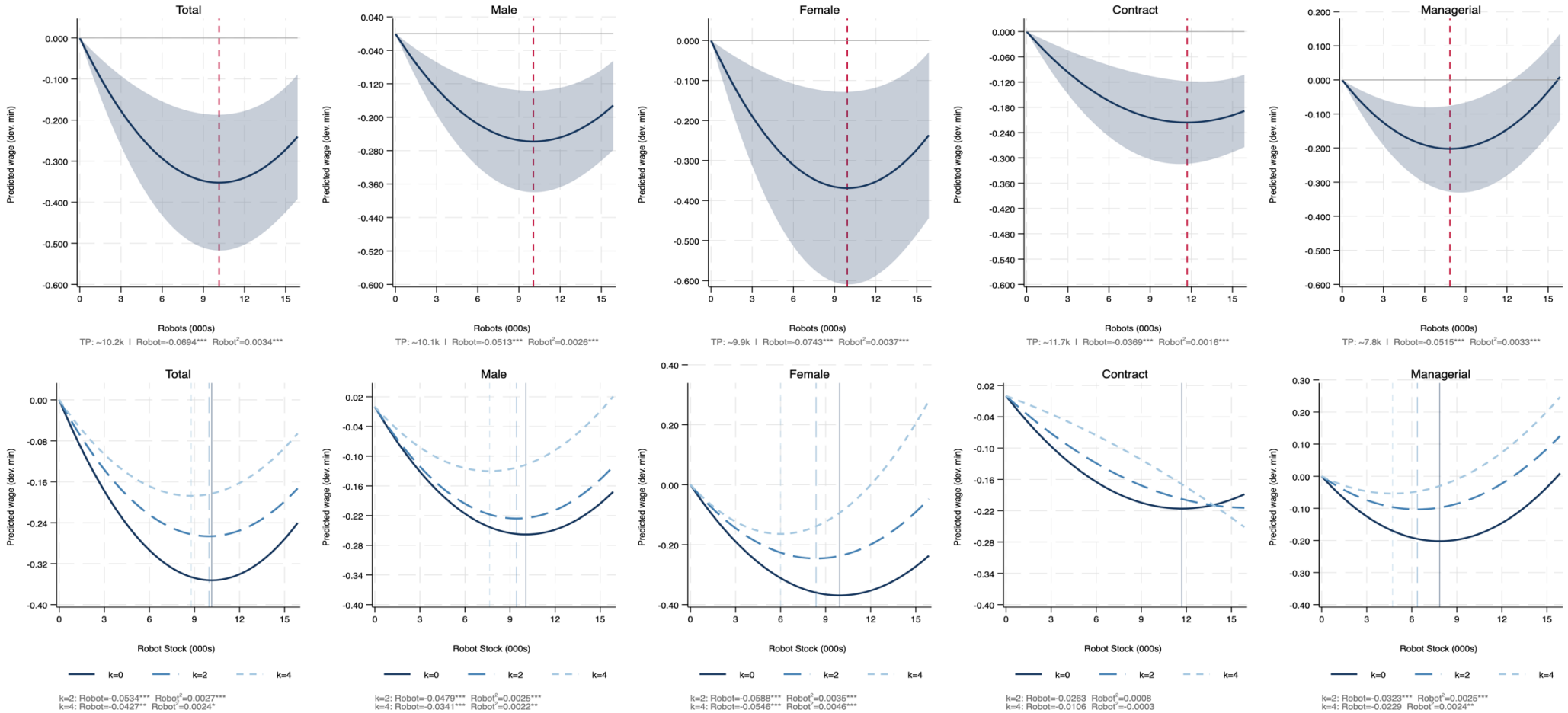
Figure 7 presents our results using the OLS method. The first row presents predicted wage & salaries deviation from the lowest adopted industry, along with 95% confidence intervals. The second row illustrates the dynamic effect. The vertical line indicates the turning point. The first column demonstrates a U-shaped relationship between total wages & salaries per employee and robot adoption. Initially, the remuneration per employee falls sharply till 10,200 units of robots, and then rises slightly. This turning point is the same as in what we observed for total employment. A 10,200 units of additional robot installation than the minimum adopted industry is associated with 35% drop in wages & salaries per employee. An additional 5,000 units improves it by 10%. When comparing high- and low-adoption industries, remuneration per employee has dropped significantly in high-adoption industries. These patterns continue for the period $k > 0$ as well.

Column 2 and 3 provide results for wages per male workers and wages per female workers, respectively. It drops sharply at the initial stage of adoption, then improves slightly around 10,000 robots. While comparing the magnitude of the effects, female workers experience a higher wage drop. The predicted deviation at the turning point is –25% and –37% for males and females, respectively. It indicates that although female workers do not experience a decline in their employment share, they feel the agony of robotisation through lower wages.

The fourth column shows the results for contract workers' wages. It suggests that contract workers experience an immediate wage decline following the installation of robots. Even though robotisation increases the number of contract jobs, it also reduces their wages. Therefore, one possible reason for hiring more contract workers is that they are relatively cheap due to weaker bargaining power and lower job security.

In contrast, the last column reveals a different pattern for supervisory and managerial staff. Although their salary initially decreases, it immediately reverses. In other words, employees in supervisory and managerial roles receive higher salaries immediately at the higher tail of robotisation. Although their share of total employment declines, the remaining employees benefit from higher remuneration. Their higher salary may indicate they are responsible for managing and coordinating automated production processes. In a nutshell, our findings suggest that robots generate heterogeneous wage effects across employee groups.

Figure 7: Robots on wages and salaries



Row 1: predicted log wage deviation from lowest-adoption industry. OLS estimates.
Row 2: overlaid predicted curves across horizons.

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4.4. Heterogeneity analysis.

The above results establish a significant impact of robots on employment, workforce composition, and wages. This subsection studies whether these effects vary across plants with different characteristics. To study this, we re-estimate equation 2 for subgroups defined along eight dimensions: export orientation, R&D activity, ISO certification, foreign ownership, worker training, rural versus urban location, plant age, and plant size. The results are presented in Figure 8 to Figure 12 in two rows: the top row shows predicted worker-group employment shares, and the bottom row shows predicted wages or salaries per worker for the corresponding groups, along with 95 per cent confidence intervals. To test whether employment shares and wages differ statistically across groups within each dimension, we report the p-value from a Wald test of the equality of the Robot and Robot2 coefficients.

We first split each industry into exporters and non-exporters, and Figure 8 presents the results for both groups. The share of male workers drops significantly in both groups due to robot penetration; however, the relative magnitude of the decline is small. Their wages drop more severely among non-exporters compared to exporters, and the difference is statistically significant. There is no significant difference in female employment or in the contract workers' share between the two groups. The wages of contract workers declined sharply among non-exporters, reflecting weaker bargaining power in domestically oriented plants. Finally, we did not find much difference between the shares and salaries of supervisory & managerial staff between the groups.

Figure 9 distinguishes plants that provide formal worker training to their employees from those that do not. We find that both male worker shares and wages drop significantly more among the non-training group compared to their counterpart. Regarding contract workers, the non-training group's share increases while wages decrease. It implies that firms' investment in skills does not replace permanent workers outright with robots or contract staff. The investment in skills probably enables firms to redeploy workers across tasks rather than replace them (Acemoglu & Restrepo, 2019). As a result, the decline in their wages is significant in the non-training group. Among supervisory and managerial staff, a significant drop in share and wage was observed only for the non-training group. These patterns point to employee training as a mechanism through which plants can moderate both the displacement and wage-compression effects of automation. We find a similar pattern between ISO-certified and non-certified groups in Figure 10. The non-certified group exhibits a significant decline in employment share and wages. employees. This correspondence is possible since quality

certification and employee training tend to co-occur and both proxy for the adoption of complementary organisational practices.

Figure 11 presents results for domestic firms and for firms with foreign ownership. We find that domestic firms experience a decline in the male share, whereas foreign firms experience an increase in the male share. This result is opposite for contract workers. An increase in share is observed in domestic firms, whereas a decrease in share is observed in foreign firms. These differences are statistically significant. Regarding wages, contract workers experience a significantly higher drop in domestic groups compared to foreign groups. We also find that supervisory & managerial staff receive significantly higher salaries in the foreign group compared to the domestic group. Figure 12 present result for firms located in rural and urban areas. The male share of employment dropped significantly more in urban areas than in rural areas. Another important observation is that wages for contract workers are significantly reduced in rural plants compared to those in urban plants. It is observed that the contract shares for both rural and area increases.

Figure 8: Exporters vs non-exporters



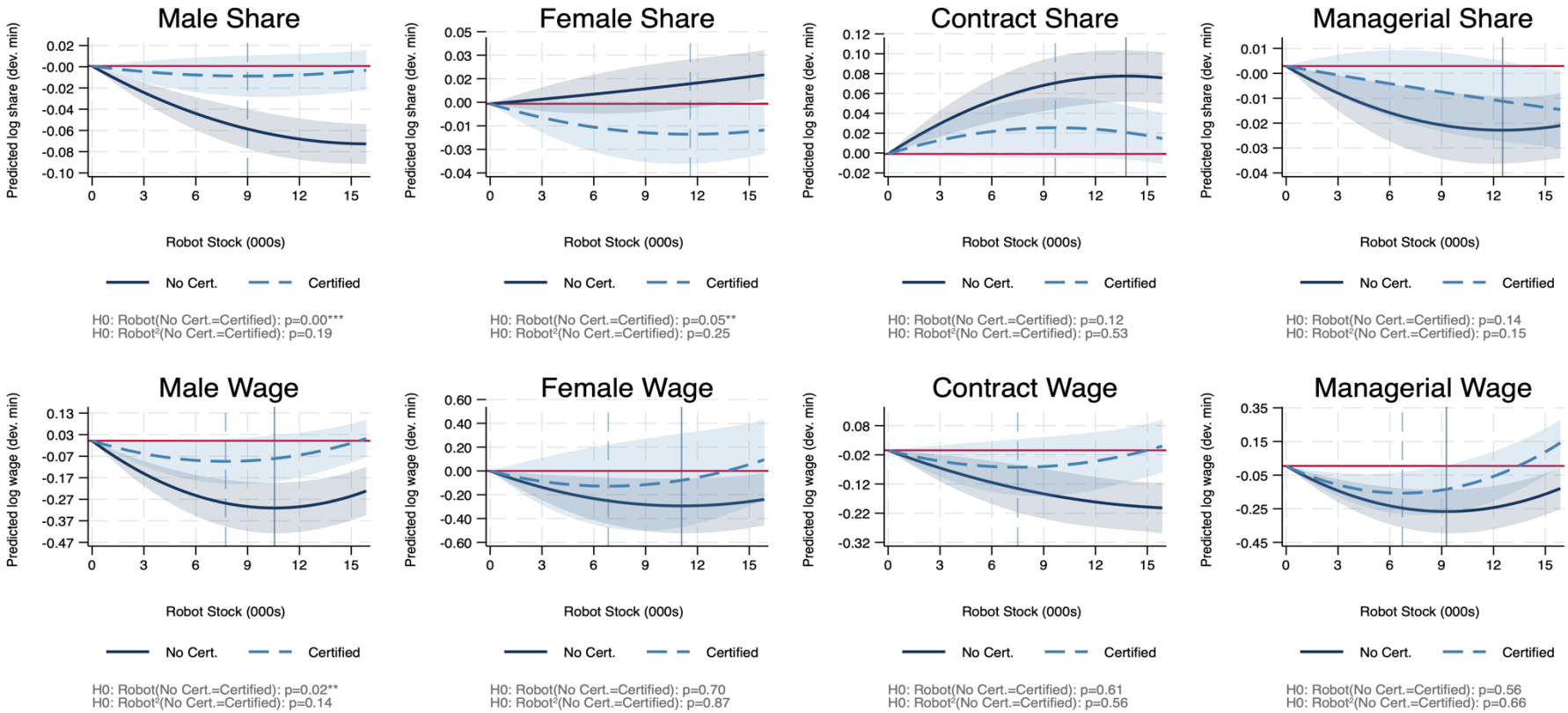
Row 1: Employment Shares. Row 2: Wages.
Wald test p-values (suest) for equality of coefficients across groups.
Shaded bands: 95% CI. Vertical lines: turning points.

Figure 9: Training vs non-training firms



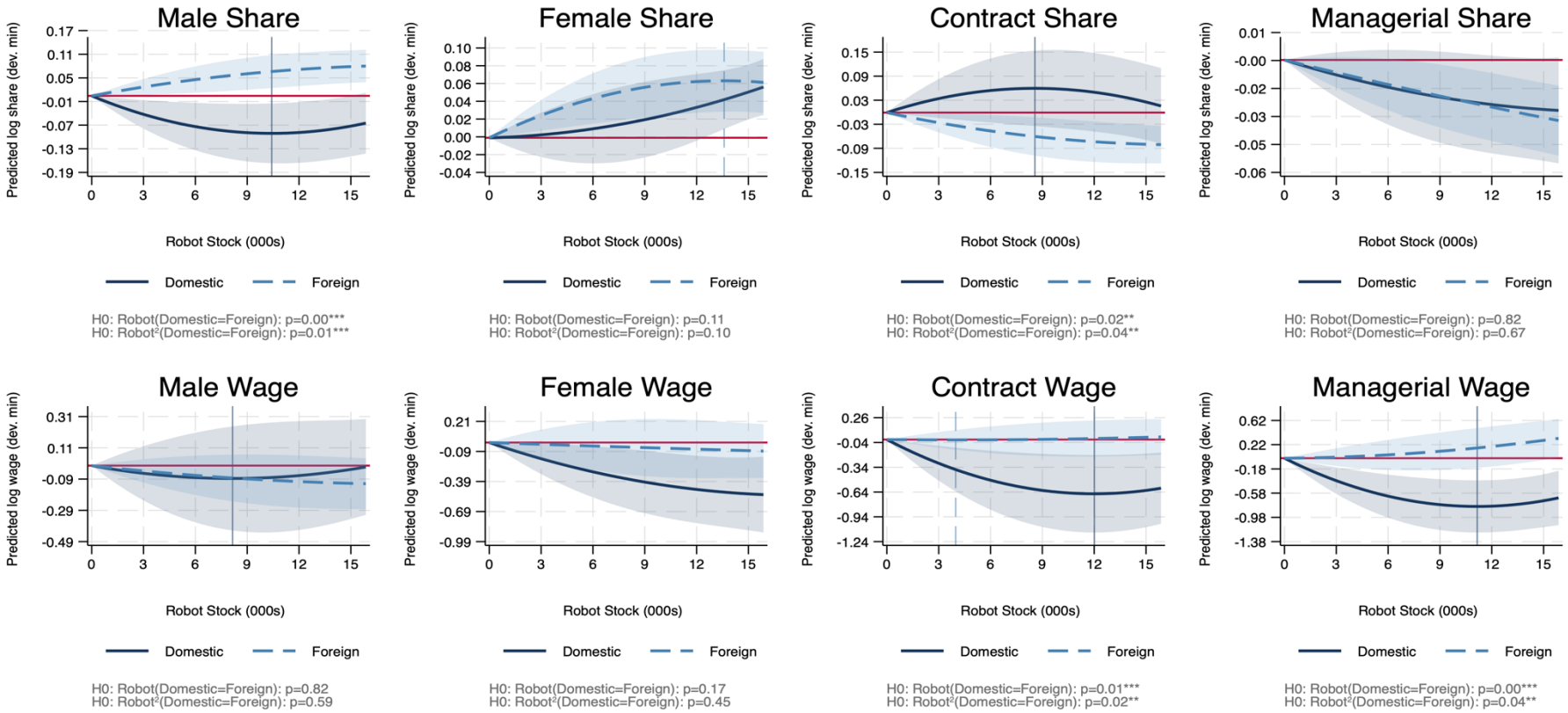
Row 1: Employment Shares. Row 2: Wages.
Wald test p-values (suest) for equality of coefficients across groups.
Shaded bands: 95% CI. Vertical lines: turning points.

Figure 10: ISO certified vs non-certified



Row 1: Employment Shares. Row 2: Wages.
Wald test p-values (suest) for equality of coefficients across groups.
Shaded bands: 95% CI. Vertical lines: turning points.

Figure 11 Domestic vs foreign



Row 1: Employment Shares. Row 2: Wages.
Wald test p-values (suest) for equality of coefficients across groups.
Shaded bands: 95% CI. Vertical lines: turning points.

Figure 12 Urban vs rural



Row 1: Employment Shares. Row 2: Wages.
Wald test p-values (suest) for equality of coefficients across groups.
Shaded bands: 95% CI. Vertical lines: turning points.

5. Conclusion

Although automation technologies such as industrial robots have been growing globally, their role in labour market dynamics is not well documented in developing countries. This paper fills the gap by analysing the effects of industrial robot adoption on employment, workforce composition, and wages in the Indian manufacturing sector. We combine two complementary data sources to study these questions at the industry level. Robot adoption is measured using data from the International Federation of Robotics (IFR), which provides industry-level information on newly installed industrial robots for the period 2009–2023. Labour market outcomes are constructed from the Annual Survey of Industries (ASI). We aggregate plant-level ASI data to the two-digit industry level and match it with IFR data, yielding a balanced panel of ten industries for fifteen years.

Our findings reveal a rich and nuanced picture of the labour market consequences of robotisation in the Indian manufacturing sector. We first document that the relationship between robot adoption and total employment is nonlinear. At low levels of robot penetration, the productivity effect dominates: instrumented estimates indicate that a 1,000-unit increase in the industry robot stock is associated with a 1.2 percent increase in total employment. However, as robot penetration intensifies, the displacement effect strengthens and eventually reverses employment growth around 10,250 units. These effects are persistent, remaining statistically significant in subsequent years, suggesting that adjustments to production processes and workforce composition are gradual rather than immediate.

Further, we document a substantial heterogeneity in how different groups of workers are affected. Among permanent production workers, robot adoption drastically reduces the share of male workers but has little effect on the share of female workers. We interpret this differential effect as a reflection of the gender wage gap in India. Since firms pay higher wages to males than to females, they may have stronger incentives to substitute robots for male workers. The positive effect of robots on aggregate employment that we observed is driven mainly by an expansion of contract labour, employed indirectly through third-party agencies. Moreover, the share of supervisory and managerial staff also declines due to robotisation.

The wages and salaries effects of robot adoption are U-shaped. It reduces remuneration per employee at the initial stage, and increases at the higher end of robot adoption. We also observe that the effect is heterogeneous among different groups and persists over time. For

production workers — both permanent and contract — robot adoption initially exerts sustained downward pressure on wages. The wage decline is marginally larger for female than for male production workers and turns around at 10,000 units for robots. It suggests that while robots do not reduce the share of female workers in employment, they nonetheless share the burden of wage competition. Contract workers experience a sharp wage response, and their wages hardly rise in the higher tail. The salaries of supervisory and managerial staff turn earlier than other workers and rise sharply, reflecting increased demand for workers with the technical and organisational skills to coordinate automated production systems

AI Declaration: *During the preparation of this work, the authors used Claude.ai to correct grammar and improve sentence structure. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.*

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Appendix

Table 1A: Correspondence between IFR code and 2-digit NIC code

IFR class	Categories, divisions and classes of economic activities, ISIC, rev. 4	Definitions	NIC 2-digit Codes	NIC 2-digit Industry Name
10-12	Food products and beverages; Tobacco products		10, 11, 12	Manufacture of food products; Manufacture of beverages; Manufacture of tobacco products
13-15	Textiles, leather, wearing apparel	Textiles; Wearing apparel; dressing & dyeing of fur; Luggage, handbags, saddlery, harness and footwear	13, 14, 15	Manufacture of textiles; Manufacture of wearing apparel; Manufacture of leather and related products
16	Wood and wood products (incl. furniture)	Manufacture of wood, products of wood (incl. wood furniture) and products of cork	16, 31	Manufacture of wood and products of wood and cork; Manufacture of furniture
17-18	Paper and paper products, publishing & printing	Manufacture of pulp, paper and converted paper production, printing of products, such as newspapers, books, periodicals, business forms, greeting cards, and other materials, and associated support activities, such as bookbinding, plate-making services, and data imaging; reproduction of recorded media, such as compact discs, video recordings, software on discs or tapes, records etc.	17, 18	Manufacture of paper and paper products; Printing and reproduction of recorded media
19-22	Plastic and chemical products	Manufacture of basic pharmaceutical products and pharmaceutical preparations. This includes also the manufacture of medicinal chemical and botanical products; Transformation of crude petroleum and coal into usable products, transformation of organic and inorganic raw materials by a chemical process and the formation of products; (e.g. rubber tires, plastic plates, foils, pipes, bags, boxes, doors, etc.) rubber and plastic parts for motor vehicles should be reported in 29.3.2	19, 20, 21, 22	Manufacture of coke and refined petroleum products; Manufacture of chemicals and chemical products; Manufacture of pharmaceuticals, medicinal chemical and botanical products; Manufacture of rubber and plastics products
23	Glass, ceramics, stone, mineral products n.e.c. (without automotive parts*)	Manufacture of intermediate and final products from mined or quarried non-metallic minerals, such as sand, gravel, stone or clay, manufacture of glass, flat glass ceramic and glass products, clinkers, plasters, etc.	23	Manufacture of other non-metallic mineral products

24-28	Metal	e.g. iron, steel, aluminium, copper, chrome etc.; e.g. metal furniture, tanks, metal doors, forging, pressing, stamping and roll forming of metal, nails, pins, hand tools, etc.; e.g. machinery for food processing and packaging, machine tools, industrial equipment, rubber and plastic machinery, industrial cleaning machines, agricultural and forestry machinery, construction machinery etc.	24, 25, 28	Manufacture of basic metals; Manufacture of fabricated metal products, except machinery and equipment; Manufacture of machinery and equipment n.e.c.
26-27	Electrical/electronics		26, 27	Manufacture of computer, electronic and optical products; Manufacture of electrical equipment
29	Automotive		29	Manufacture of motor vehicles, trailers and semi-trailers
30	Other transport equipment	e.g. ships, locomotives, aeroplanes, spacecraft vehicles	30	Manufacture of other transport equipment

Table A2: Variable description

Variable Name	Definition	Source
Robot	Industry-level stock of industrial robots in industry *j* and year *t*, constructed using IFR shipment data and a perpetual inventory method. Robot stock in December of calendar year *t* is matched with ASI financial year *t+1* (March of next year).	IFR
Employment	Employment is measured as the ratio of total man-days worked to the number of working days. It includes production workers, supervisory & managerial staff, and other employees.	ASI
Male	Number of male workers.	ASI
Female	Number of female workers.	ASI
Contract	Number of workers hired through third-party contractors or agencies.	ASI
Managerial Staff	Number of supervisory and managerial employees.	ASI
Male Share	Ratio of male production workers to total employment.	ASI
Female Share	Ratio of female production workers to total employment.	ASI
Contract Share	Ratio of total production workers hired through third-party contractors or agencies to total employment.	ASI
Managerial Share	Ratio of supervisory/managerial staff to total employment.	ASI
Wages & Salaries	Total wages and salaries paid to all the workers.	ASI
Male Wage	Total wages paid to male production workers are divided by the number of male workers.	ASI
Female Wage	Total wages paid to female production workers are divided by the number of female workers.	ASI
Contract Wage	Total wages paid to contract production workers are divided by the number of contract workers.	ASI
Managerial Wage	Total salaries paid to supervisory/managerial staff are divided by the number of Managerial employees. (Deflated to constant prices.)	ASI
Borrowings	Ratio of outstanding borrowing to total fixed capital.	ASI
Size	Natural logarithm of total fixed capital.	ASI
Investment	Ratio of investment capital to total fixed capital.	ASI

Figure A1 Robots and employment (IV)

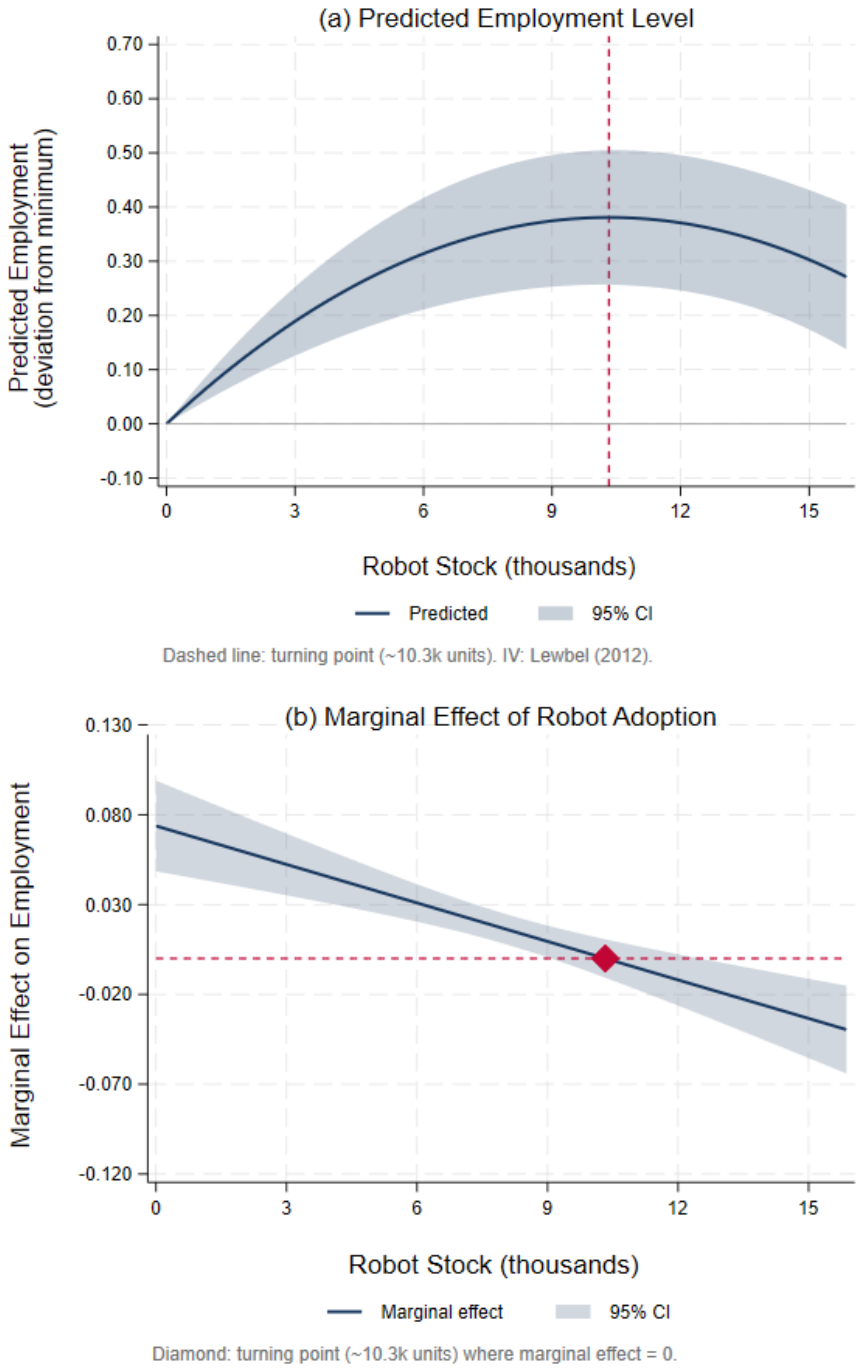
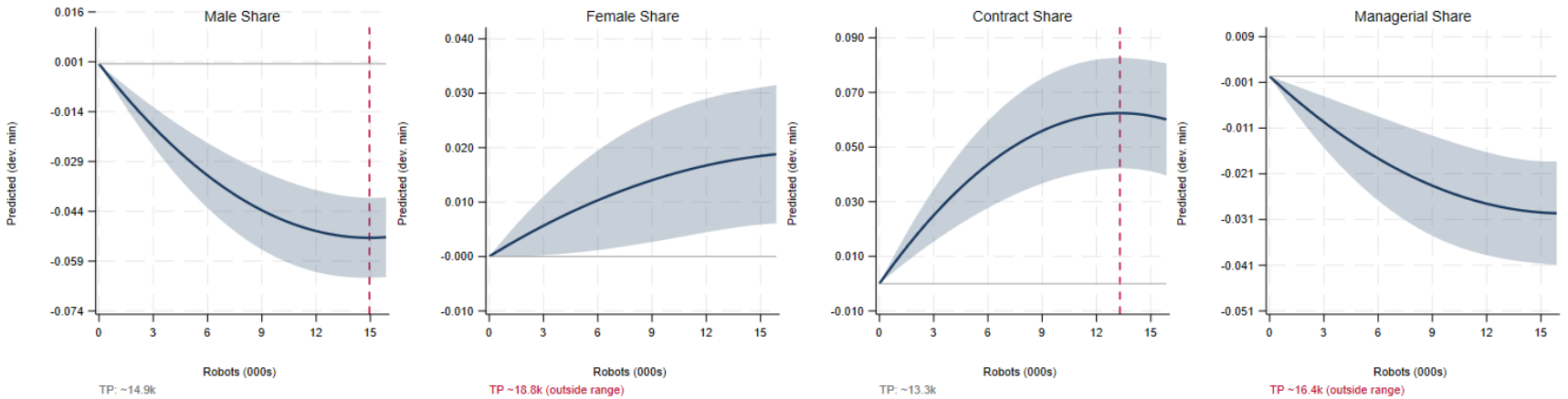
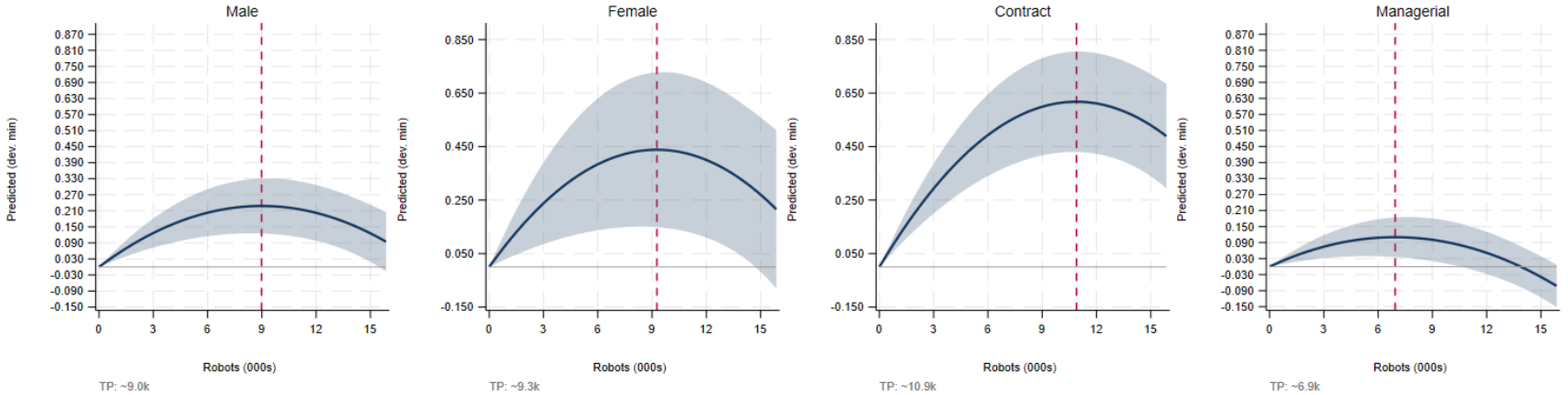


Figure A2: Nonlinear Effects of Robot Adoption on Workforce Composition (IV)

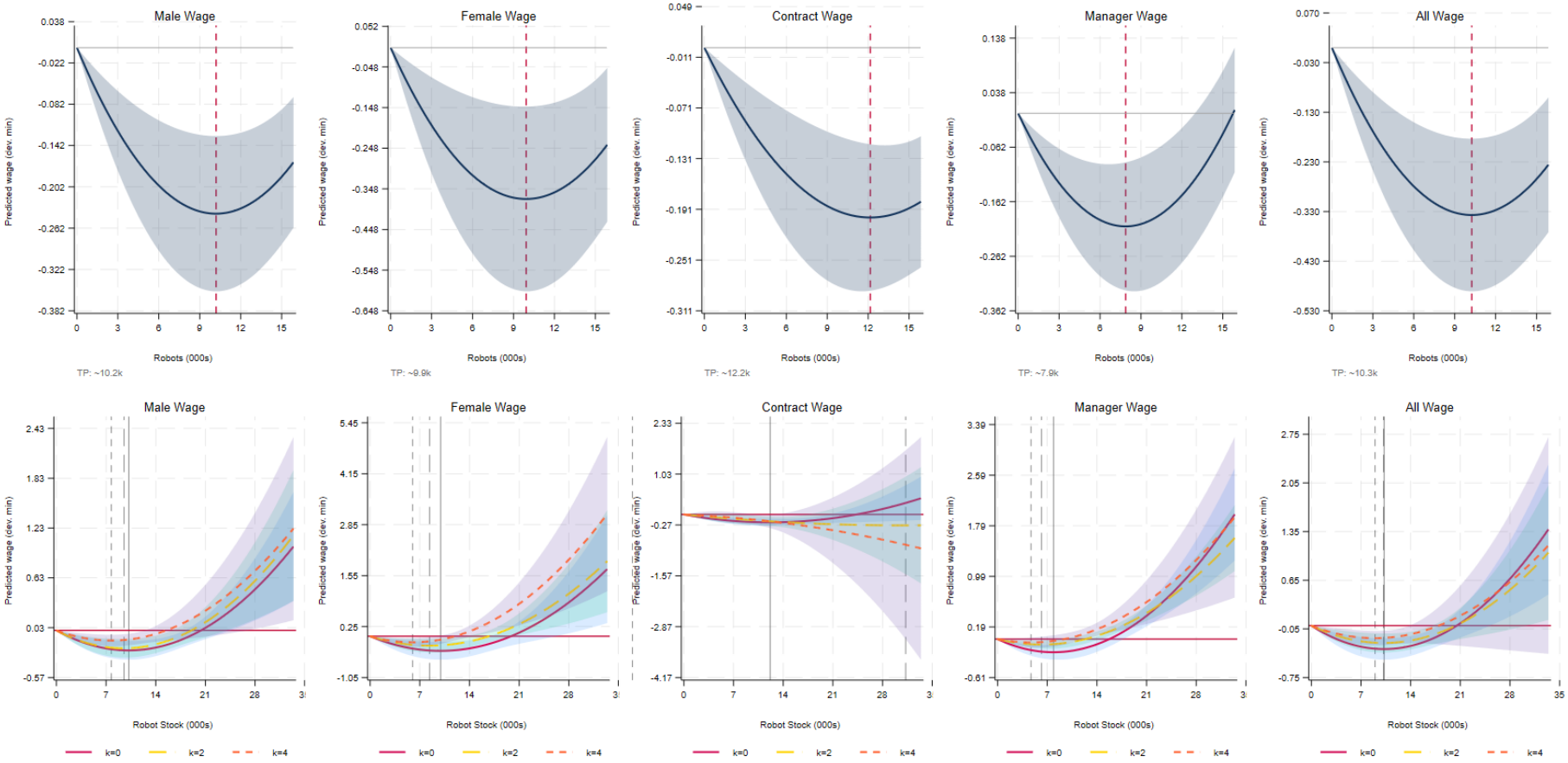


Y-axis: deviation from lowest-adoption industry. Dashed line: turning point.
Shaded band: 95% CI (delta method). IV: Lewbel (2012).



Y-axis: deviation from lowest-adoption industry. Dashed line: turning point.
Shaded band: 95% CI. IV: Lewbel (2012).

Figure A3: Robots on wages and salaries (IV)



Row 1: predicted log wage deviation from lowest-adoption industry. IV: Lewbel (2012).
Row 2: overlaid predicted curves across horizons.